Alleviating Issues in Iris Recognition using Deep Learning Paradigm

Synopsis of the Thesis to be submitted in Partial Fulfillment
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by

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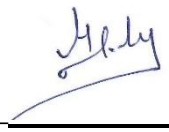
Signature of the Student: 

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This is to certify that the thesis entitled **"Alleviating Issues in Iris Recognition using Deep Learning Paradigm"**, submitted by **Meenakshi Choudhary (Roll No. 175000103)** to International Institute of Information Technology, Naya Raipur, is a record of bonafide research work under our supervision and we consider it worthy of consideration for the Synopsis of the Thesis to be submitted in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy of the Institute.

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Abstract

Despite the prominence of iris-based human recognition, several issues inhibit the wide-scale deployment of Iris Recognition (IR) systems. Such issues include unconstrained iris acquisition using heterogeneous cameras/ sensors, presentation attacks, contact lenses, and visible spectrum-based iris imaging. This study aims to mitigate such problems using deep learning methodology. Indeed, IR systems without administrators are more susceptible to Presentation Attacks (PAs) that obstruct their usual functioning. Such PAs may be launched using substances such as printed iris images, artificial eyeballs, synthetic irises, cosmetic contact lenses, etc. Further, the soft lens may increase the false rejection rate as it blurs the iris texture within the eye image. In this vein, we formulate three distinct problems; contact lens discrimination, textured lens-based Presentation Attack Detection (PAD), and PAD with a medley of known and unknown attacks. This work mitigates such problems using the score-level fusion of handcrafted and data-driven features. However, we further extend this method by replacing the generic features with domain-specific features and observed significant performance improvement for the same problem. It proves the strength of domain-specific features over generic features. Further, to realize PAD, this work applies a feature selection and fusion approach on the region of interest (RoI) detected by the YOLO-based framework. The proposed approach examines several handcrafted and data-driven features using the Friedman test to identify k-most discriminatory features and combines them using score-level fusion. The experimental outcomes on six distinct datasets unveil that this method outperforms the existing methods.

The use of heterogeneous (cross) sensors during iris enrollment and recognition may result in false rejection. This study introduces an ensemble architecture exploiting the convolutional and residual models with an effective regulation mechanism to overcome such problem. The method achieves two least error rates as 1.06% and 1.21% and outperforms the state of the arts (SOTAs). Besides, visible spectrum-based iris imaging is realized through a new iris verification scheme based on a sandwiched Siamese architecture, which examines normalized iris pairs and learns a similarity score based on their relational features. Moreover, it employs a normalized correlation layer to handle the noise within the iris images. The proposed approach is evaluated on two public iris datasets; MICHE-I and MICHE-II datasets, where it achieves a genuine match rate GMR > 97% and equal error rate EER <1%.

Keywords: Iris recognition, Iris verification, Presentation attack detection, Contact lens detection, Unconstrained iris acquisition, Visible spectrum iris recognition, CCRNet, DCCNet, Sandwiched Siamese network, Deep learning.

CHAPTER-1: Introduction and Literature Review

1.1 Iris Recognition

Iris recognition is a method of automated person recognition based on his/her iris texture [1]. The term 'texture' represents the iris attributes in terms of regularity, coarseness, homogeneity, directionality, etc. The human iris owns some exceptional characteristics such as rich morphological structure, definite uniqueness for each individual (even twins), inimitability, stability over time, etc., that makes it more adequate compared to other biological identities [2].

1.2 Iris Recognition System

An Iris Recognition (IR) system compares two iris images to produce a match score depicting their degree of similarity or dissimilarity [1-2]. It works in two separate phases; enrollment and authentication as depicted in Figure 1.1. An individual's iris features are registered in the database during enrollment, whereas the authentication phase compares the person's iris features with stored templates to make a decision. The several modules of an IR system are described below:

Iris Acquisition: In this module, the person's iris image is captured through a camera/sensor in the near infrared spectrum. Usually, a sequence of iris images are captured and merely a few images are considered after evaluating their quality of features. They typically contain significant iris textural information for further processing.

Segmentation: The segmentation module localizes the iris region within the eye image by detecting the inner and outer iris boundaries. Other eye regions include the sclera, pupil, eyelids, and eyelashes.

Normalization: The segmented iris region undergoes a normalization phase to transform the iris texture within the annular region from Cartesian coordinates to pseudo polar coordinates via a rubber sheet model.

Feature Extraction and Matching: While the unwrapped iris may be directly used to compare two irides (e.g., by using correlation filters); typically, a feature extraction routine is used to encode its textural content.

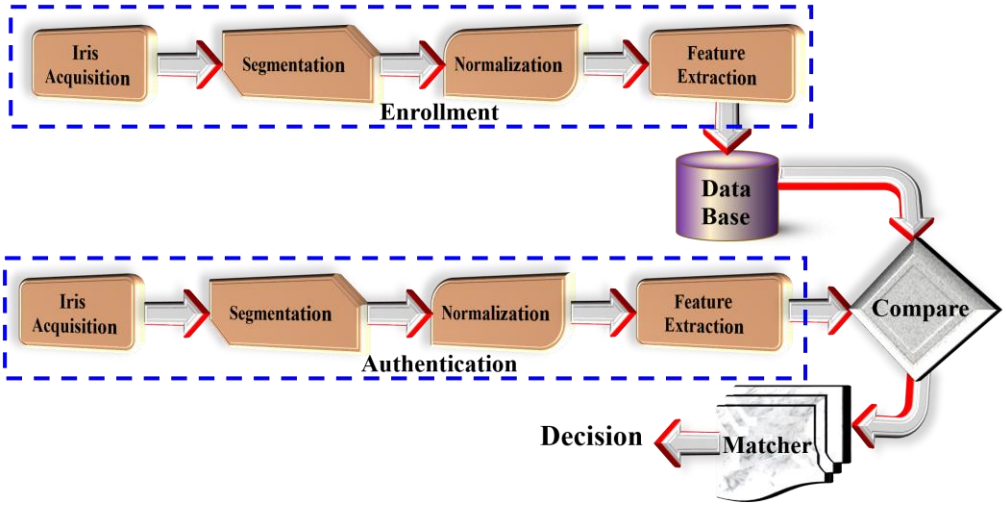


Fig. 1.1 Illustration of process workflow within the Iris Recognition System

1.3 Literature Review

A comprehensive review of iris related literature unveils that several issues greatly obstruct the wide-scale deployment of IR systems. The Presentation Attacks (PAs) through cosmetic contact lenses, printed iris images, and synthetic irises may forge a legitimate identity to access the system [3]. Various handcrafted techniques [3, 4] have been introduced for iris Presentation Attack Detection (PAD). However, they use empirically defined parameters, not adequate for intra-class variations within iris samples. Further, some deep-learning models were also introduced that employ Convolutional Neural Networks (CNNs) and Residual networks for iris feature extraction [5]. In recent years, fusion-based methods were proposed, where multiple handcrafted and data-driven features are combined to produce discriminatory features for iris PAD [6, 7]. Some of the abovementioned methods focus on merely contact lens detection within human eyes, while others include all known and unknown iris PA variants.

Another issue includes heterogeneous sensors for iris acquisition in an unconstraint environment, where the captured iris images may contain noisy factors and varying textural qualities. The machine learning techniques have consistently being used for iris pattern recognition with one or more local and/or global iris feature descriptors [3, 4]. Recently, deep-learning based models were developed for heterogeneous iris recognition [2, 8]. Although these models reported pleasant performance for single-sensor setup, there is still an urge for improving cross-sensor iris recognition.

Further, iris imaging in the visible spectrum results in unidentifiable iris texture within the captured images, yielding lower recognition accuracy. Several works [9, 10] employed sparse representation for pattern recognition, whereas few works [9, 11] utilized deep CNN models. Such techniques may result in high recognition accuracy in visible spectrum-based iris recognition. However, CNN is a multi-class network that employs a gradient descent optimizer during backpropagation that typically suffers from local minimum point problems.

1.4 Motivation and Objectives

The motivation for this work occurred due to the unique characteristics of the iris such as the uniqueness in the iris texture, stability over time, inimitability, etc. However, the literature explains several issues that compromise the identification accuracy. Therefore, this study focuses to enrich the iris recognition technology for its wide-scale deployment by alleviating the current issues. Indeed, this work is aimed to fulfill the following objectives:

- To prevent the forgery of iris patterns through textured contact lenses during enrollment and authentication by developing a contact lens detection mechanism.
- To provide countermeasures against presentation attacks to prevent betraying the IR systems.
- To enhance the adaptability of IR systems towards heterogeneous cameras/sensors to enable their wide-scale deployment.
- To provide flexibility to the users to provide iris signatures in an unconstrained manner, e.g. from varying distances, angles, and illumination conditions.
- To accomplish accurate iris verification in the visible spectrum. It can significantly drive the use of iris-based user verification in smartphones.

1.5 Problem Statements

Contact Lens Detection and Discrimination: Using textured contact lenses, an individual may register himself with fake iris signatures [3, 6]. Besides, the soft lens may increase the false rejection rate by making the iris texture blur. Therefore, it is foremost to detect contact lenses in human eyes.

Presentation Attack Detection (PAD): The substances such as artificial eyeballs, synthetic irises, or textured contact lenses may be utilized to launch iris presentation attacks [5, 7]. Thus, a presentation attack detection (PAD) mechanism is required to differentiate between the real iris and attack patterns.

Heterogeneous-sensor Iris Recognition in Unconstraint Environment: In general, users enrolling in the IR system with a certain sensor may encounter a distinct sensor during authentication. The variance in the textural qualities of iris images captured through distinct sensors possess a huge intra-class variance and eventually increases the false rejection rate (FRR) [2, 8].

Iris Recognition in Visible Spectrum: The iris-based user authentication in smartphones needs visible spectrum iris imaging through the smartphone camera [4]. However, the visibility of iris microstructures within the visible spectrum is not clear, which reduces the iris recognition accuracy [9, 11].

1.6 Research Contribution

This research contribution of the proposed work from technical aspects are listed below:

- The study introduces a fusion-based methodology for contact lens detection, where a deep-learning based model is combined with two handcrafted methods for iris feature extraction. This model is a customized Densenet121 model, which is trained on iris images.
- This work demonstrates the potential of domain-specific features over generic features. Two distinct filters trained on iris images are employed for feature extraction to enrich textured lens-based PAD and contact lens discrimination.
- Further, it develops a deep-learning based model using convolutional and residual blocks and ensembles it with existing statistical methods to improve cross-sensor iris recognition.
- It develops a fusion-based PAD method to handle both known and unknown attacks and also provides a different insight to the prominent Friedman test to utilize it for feature extraction.
- It introduces an iris verification mechanism for smartphones by using a sandwiched Siamese model where the iris feature similarity is evaluated through a normalized cross-correlation layer.

1.7 Applications of the Study

This work is carried out after emphasizing various applications demanding iris biometrics as below:

- Some factors such as the assimilation of iris scanners in smartphones, the rise in the use of iris biometrics in government projects, increasing cases of fraudulent activities, and security compromises and have increased the demand for iris based person recognition.
- Due to the increasing number of distribution channels, research and development initiatives, and increased adoption in enterprises have encouraged to enrich the iris recognition technology.
- The iris biometrics has attained its applications in the field of healthcare, military and defense, government organizations and projects, and in the end user's industries.

CHAPTER-2: Textured Lens based Iris PAD and Contact Lens Discrimination[1]

2.1 Introduction

As mentioned in the previous chapter, an Iris Recognition (IR) system can be deceived by contact lenses. Therefore, a contact lens detection mechanism needs to be deployed prior to the IR system, which is aimed to discriminate between the real iris and contact lenses [3, 6]. The input sample may belong to normal (real) iris, textured lens or soft lens as depicted in Fig. 2.1.

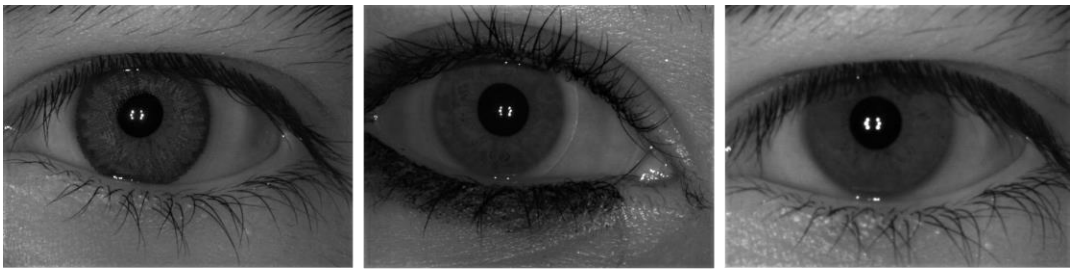


Fig. 2.1 Samples of human eyes representing iris with the textured, soft, and normal lenses.

2.2 Proposed Technique: Fusion of DCCNet with Handcrafted Methods

The proposed fusion approach is depicted in Fig. 2.2 that incorporates a CNN model along with two handcrafted feature descriptors, i.e. Scale Invariant Descriptors (SID) [4] and DAISY [6]. The CNN model is a customized version of DenseNet121 [12] with merely first two dense blocks and two output classes at the last fully connected layer (since PAD has two output classes). It is re-trained on the iris dataset to learn iris features. The customized model is depicted in Fig. 2.3 and is referred to as "Densely-connected Contact-lens Classification Network (DCCNet)". The DCCNet aids in diversified high-level feature construction, while the statistical features are twisted through the feature descriptors that extract local as well as global micro-structures.

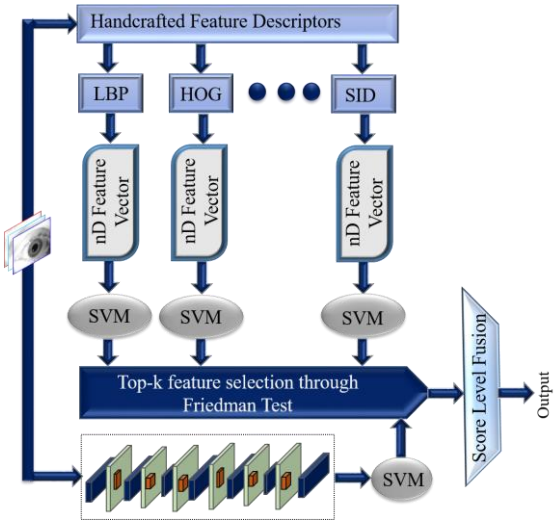


Fig. 2.2 Feature level fusion of DCCNet and statistical methods for PAD and contact lens discrimination.

[1] Choudhary, M., Tiwari, V. and Venkanna, U., 2020. Iris anti-spoofing through score-level fusion of handcrafted and data-driven features. Applied Soft Computing, 91, p.106206.

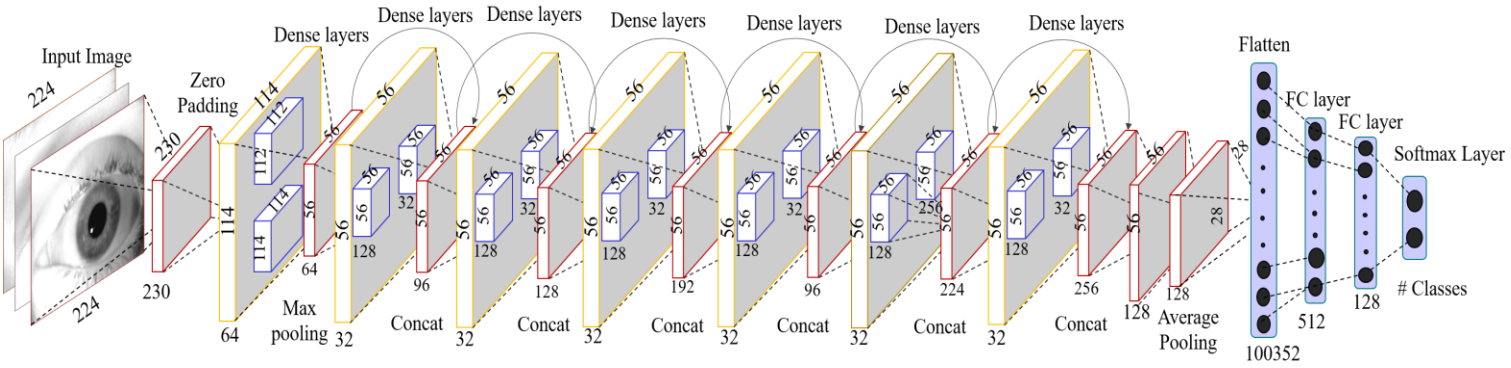


Fig. 2.3 The layered architecture of proposed DCCNet model, depicting the dimensions of output feature maps from each layer.

2.3 Experimental Setup and Results

2.3.1 Datasets

- ND Cosmetic Contact Lens 2013 with ND-I and ND-II sensors [13]
- IIITD Contact Lens with Cogent and Vista sensors [14]
- Clarkson 2017 [15]

2.3.2 Protocols for Method Assessment

Single-sensor Validation: In this validation protocol, the proposed approach is trained and tested on iris samples captured from the same sensor. The experimental outcomes are given in Table 2.1.

Cross-sensor Validation: This validation includes dual sensors, i.e., training and testing are carried out individually on two distinct sensor datasets, while the sensor pairs are twisted on the sole dataset. The experimental outcomes are given in Table 2.2.

Table 2.1 Single-Sensor Validation (All entries are in %)

Exp.	Dataset	Proposed			SoTA Results	RW
		EER (‡)	Accuracy (*)	ACER (#)		
Attack vs Real	Cogent	1.87	98.71	1.61	1.57#	[6]
	Vista	0.39	99.30	0.20	0.22#	
	ND-I	0.22	97.95	0.18	0.5#	
	ND-II	2.02	96.85	2.18	2.0#	
	Clarkson	3.08	95.33	2.98	3.25#	
Textured vs Normal	Cogent	0.63	98.91	0.87	5.5#	[7]
	Vista	0.18	99.98	0.21	0.7#	
	ND-I	0.27	98.01	0.24	0.41#	[3]
	ND-II	1.39	97.12	1.19	0.37#	[16]
Textured vs Soft vs Normal	Cogent	2.57	96.24	2.59	95.20*	[17]
	Vista	1.33	97.13	1.27	95.36*	
	ND-I	2.64	94.25	2.81	92.95*	
	ND-II	3.52	95.81	3.28	95.74*	
Textured vs Soft	Cogent	1.03	98.95	1.12	-	-
	Vista	0.38	99.12	0.31	-	
	ND-I	1.02	98.81	0.98	-	
	ND-II	2.03	96.93	2.22	-	
Soft vs Normal	Cogent	2.67	95.32	2.81	20.28‡	[16]
	Vista	1.52	97.13	1.39	15.64‡	
	ND-I	2.00	96.88	2.13	-	
	ND-II	3.03	95.86	3.24	-	

Note: SoTA-State of the Arts. RW: Related work.

Table 2.2 Cross-Sensor Validation (All entries denote EER %)

Exp.	Dataset	**Proposed**	SoTA Results		
			BSIF MLP [17]	SID MLP [4]	VGG-8 [6]
Attack vs Real	Cogent → Vista	**2.81**	28.55	5.75	7.12
	Vista → Cogent	**3.07**	33.61	5.44	10.51
	ND-I → ND-II	**1.82**	23.33	3.32	4.79
	ND-II → ND-I	**4.62**	21.09	6.76	11.48
Textured vs Normal	Cogent → Vista	**1.35**	28.11	3.01	3.81
	Vista → Cogent	**2.24**	30.23	4.76	5.91
	ND-I → ND-II	**1.39**	23.9	2.11	4.33
	ND-II → ND-I	**3.66**	17.53	5.33	8.98
Textured vs Soft vs Normal	Cogent → Vista	**2.91**	25.47	3.66	4.11
	Vista → Cogent	**3.04**	26.31	5.99	8.71
	ND-I → ND-II	**2.74**	21.56	4.67	2.99
	ND-II → ND-I	**4.43**	18.77	7.81	12.22
Textured vs Soft	Cogent → Vista	**1.81**	26.32	4.46	6.31
	Vista → Cogent	**2.59**	29.78	6.01	8.44
	ND-I → ND-II	**1.14**	19.33	3.91	4.41
	ND-II → ND-I	**4.07**	20.71	5.51	10.0
Soft vs Normal	Cogent → Vista	**3.07**	28.32	7.22	8.22
	Vista → Cogent	**2.59**	30.55	7.99	12.3
	ND-I → ND-II	**2.80**	23.11	6.11	6.11
	ND-II → ND-I	**4.10**	19.23	8.23	13.77

Table 2.3 Combined-Sensor Validation (All entries denote EER%)

Exp.	Dataset	SoTA Results			
		Proposed	BSIF MLP [17]	SID MLP [4]	VGG-8 [6]
Attack vs Real	IIITD-combined	**3.11**	23.10	4.61	7.21
	ND-combined	**4.89**	26.8	3.98	9.12
Textured vs Normal	IIITD-combined	**1.12**	16.67	2.74	4.12
	ND-combined	**1.75**	17.21	3.73	3.66
Textured vs Soft vs Normal	IIITD-combined	**2.52**	25.47	6.21	7.99
	ND-combined	**6.91**	28.68	8.78	9.44
Textured Vs Soft	IIITD-combined	**2.10**	21.33	2.90	6.12
	ND-combined	**3.05**	20.42	4.93	6.91
Soft Vs Normal	IIITD-combined	**3.81**	32.15	4.23	5.02
	ND-combined	**6.16**	29.10	8.07	8.11

Combined-sensor Validation: This approach combines images from different sensors within the same dataset. Thus, the Cogent and Vista images are combined to create the IIITD-Combined dataset. Likewise, ND-I and ND-II images build the ND-Combined dataset. The experimental setup for combined-sensor validation and results are given in Table 2.3.

2.4 Summary

This chapter introduces a novel method based on the fusion of handcrafted and data-driven features to improve textured lens-based iris PAD and contact lens discrimination. This approach also enriched the state of the arts for iris PAD and contact lens classification on three preeminent iris datasets. However, the proposed method employs merely one domain-specific filter based method, i.e., DCCNet, while other methods utilize the empirically defined parameters to construct important iris features. In the next chapter, we examine two distinct learning-based feature extraction methods, both containing domain-specific filters. It further increases the performance benchmarks for textured lens-based iris PAD and contact lens discrimination.

CHAPTER-3: Iris Contact Lens Discrimination through Fusion of Domain-specific Features[2]

3.1 Introduction

This chapter is an extended version of the previous one with a more adequate methodology for textured lens based presentation attack detection and contact lens discrimination [9]. In specific, it performs score-level fusion of two distinct domain-specific feature extraction methods, i.e., multiple BSIF [18] and DenseNet. The term "domain-specific" refers to the methods, which are trained on application-specific data (iris in this case). The experimental analysis demonstrates the potential of domain-specific filters over generic filters to discriminate live iris from the artifacts. In addition, the necessity of fusion is also ascertained by comparing the fusion outcomes with individual domain-specific methods.

3.2 Proposed Approach: Score-level Fusion of Domain-specific Features

The proposed approach includes the DCCNet model due to its noble performance in the previous work. The DCCNet weights are domain-specific since it is retrained with iris images. Figure 3.1 depicts the proposed methodology, where the DCCNet features are pooled with Multiple BSIF (MBSIF) features [18]. The MBSIF method applies three BSIF filters of scales 5×5, 7×7, and 17×17 with 8, 10, and 12 bits, respectively, on raw eye image and the normalized iris image and the respective feature vectors are combined using feature-level concatenation. Besides, DCCNet extracts feature from the raw eye image. The Support Vector Machine (SVM) classifier is used to produce the local score based on the feature vectors whereas, the actual outcome is computed through the score-level fusion of local scores of all SVM classifiers.

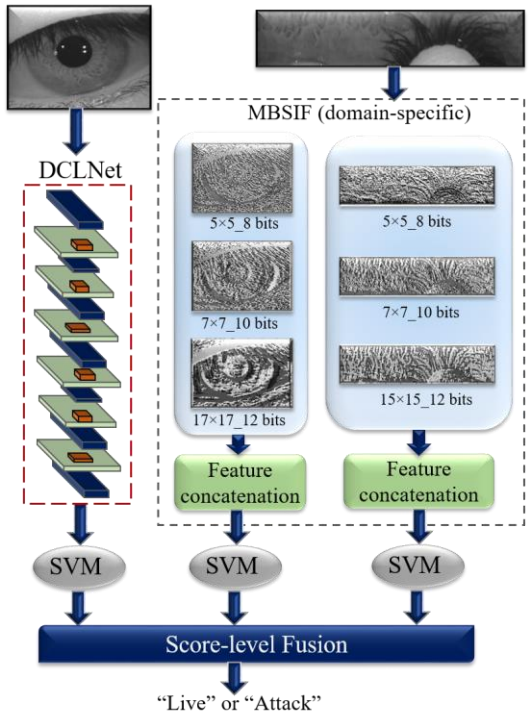


Fig. 3.1 The proposed iris liveness detection model and testing procedure.

[2] Choudhary, M., Tiwari, V. and Venkanna, U., 2020. Iris Liveness Detection Using Fusion of Domain-Specific Multiple BSIF and DenseNet Features. IEEE Transactions on Cybernetics.

3.3 Experimental Setup and Results

3.3.1 Datasets

- ND Cosmetic Contact Lens 2013 with ND-I and ND-II sensors [13]
- IIITD Contact Lens with Cogent and Vista sensors [14]
- Clarkson 2017 [15]

3.3.2 Validation Protocols

Single-sensor Validation: In this validation protocol, the proposed approach is trained and tested on iris samples captured from the same sensor. Table 3.1 delineates the experimental outcomes and compares the proposed fusion-based method with various state of the arts (SoTA).

Cross-sensor Validation: This validation includes dual sensors, i.e., training and testing are carried out individually on two distinct sensor datasets, while the sensor pairs are twisted on the sole dataset. The proposed method is compared with two SOTA methods, i.e., generic MBSIF [19] and domain-specific MBSIF [18] in Table 3.2. Besides, the individual outcomes of the DCLNet model are included for comparative analysis.

Combined-sensor Validation: This approach combines images from different sensors within the same dataset. Thus, the Cogent and Vista images are combined to create the IIITD-Combined dataset. Likewise, ND-I and ND-II images build the ND-Combined dataset. The experimental setup for combined-sensor validation and results are given in Table 3.3. The generic MBSIF [17] and domain-specific MBSIF [18] methods are again included for comparative analysis.

Table 3.1 Proposed Method's Outcomes for Single-Sensor Validation

Exp.	Dataset	**Proposed**			DCLNet Results	SoTA Results	RW
		EER (‡)	Accuracy (*)	ACER (#)			
Live vs Attack	Cogent	0.91	99.11	0.86	1.19	$1.57^{\#}$	[6]
	Vista	0.00	100	0.00	0.00	$0.22^{\#}$	
	ND_1	0.12	99.98	0.0	1.32	$0.5^{\#}$	
	ND_2	1.67	98.39	1.59	4.74	$2.0^{\#}$	
	Clarkson	2.11	98.07	2.34	2.97	$3.25^{\#}$	
Live vs Textured	Cogent	0.27	99.86	0.41	0.98	$5.5^{\#}$	[7]
	Vista	0.00	100	0.00	0.00	$0.7^{\#}$	
	ND_1	0.00	100	0.09	0.81	$0.41^{\#}$	[3]
	ND_2	0.59	99.74	0.47	1.95	$0.37^{\#}$	[16]
Live vs Soft vs Textured	Cogent	1.23	98.27	1.19	3.57	95.20^{*}	[17]
	Vista	0.72	98.95	0.59	2.99	95.36^{*}	
	ND_1	1.13	98.27	1.08	3.85	92.95^{*}	
	ND_2	2.37	97.86	2.12	4.78	95.74^{*}	
Soft vs Textured	Cogent	1.03	99.11	1.17	1.77	-	-
	Vista	0.00	99.96	0.10	0.69	-	
	ND_1	0.39	99.07	0.31	1.03	-	
	ND_2	1.24	98.94	1.15	1.99	-	
Live vs Soft	Cogent	1.12	98.63	1.24	2.04	$20.28^{‡}$	[16]
	Vista	0.22	99.77	0.57	0.97	$15.64^{‡}$	
	ND_1	0.83	99.59	0.69	1.12	-	
	ND_2	2.32	98.10	1.86	2.87	-	

Note: All entries are in (%). SoTA: State of the Arts. RW: Related Work.

Table 3.2 Proposed method's Outcomes for Cross-Sensor Validation

Exp.	Dataset	**Proposed**	SoTA Results		
			Generic MBSIF [18]	Domain-specific MBSIF [19]	DCLNet
Live vs Attack	Cogent→Vista	**1.17**	2.94	2.19	2.50
	Vista→Cogent	**1.42**	2.66	1.84	2.10
	ND_1→ND_2	**0.91**	2.33	2.11	1.98
	ND_2→ND_1	**2.05**	2.91	2.73	2.49
Live vs Textured	Cogent→Vista	**0.99**	1.37	1.33	1.77
	Vista→Cogent	**1.22**	2.41	2.20	1.98
	ND_1→ND_2	**0.67**	1.87	1.29	1.62
	ND_2 →ND_1	**1.17**	2.19	1.97	2.63
Live vs Soft vs Textured	Cogent→Vista	**1.99**	4.11	3.87	4.59
	Vista→Cogent	**2.12**	3.86	3.36	4.01
	ND_1→ND_2	**1.31**	4.17	3.84	4.07
	ND_2→ND_1	**2.27**	4.23	3.89	4.97
Soft vs Textured	Cogent→Vista	**1.03**	3.11	2.25	2.73
	Vista→Cogent	**1.78**	2.57	1.99	2.05
	ND_1→ND_2	**0.79**	2.54	1.52	1.33
	ND_2→ND_1	**2.44**	3.82	3.17	3.90
Live vs Soft	Cogent→Vista	**1.92**	3.97	3.41	3.08
	Vista→Cogent	**2.19**	4.03	3.72	4.19
	ND_1→ND_2	**1.55**	3.67	2.98	2.93
	ND_2→ND_1	**2.58**	3.89	3.18	5.11

Note: All entries denote EER%.

Table 3.3 Proposed method's Outcomes for Combined-Sensor Validation

Exp.	Dataset	SoTA Results			
		Proposed	Generic MBSIF [18]	Domain-specific MBSIF [19]	DCLNet
Live vs Attack	IIITD-combined	**1.62**	2.89	2.28	2.44
	ND-combined	**2.15**	3.26	3.33	3.11
Live vs Textured	IIITD-combined	**0.88**	2.11	1.80	1.59
	ND-combined	**1.10**	2.89	2.03	2.23
Live vs Soft vs Textured	IIITD-combined	**1.95**	3.16	2.55	3.01
	ND-combined	**2.89**	3.93	3.28	3.22
Soft Vs Textured	IIITD-combined	**1.19**	3.03	2.19	1.97
	ND-combined	**1.98**	3.59	3.14	2.89
Live Vs Soft	IIITD-combined	**3.10**	3.80	3.97	4.13
	ND-combined	**3.98**	4.39	4.17	4.22

Note: All entries denote EER%.

3.4 Summary

This chapter proposes a methodology that utilizes the fusion of domain-specific MBSIF and DenseNet-based features to improve textured-lens-based iris PAD and contact lens identification. The experimental analysis unveils that the domain-specific BSIF features are more robust than the generic BSIF features. Since MBSIF and DCLNet are both specifically trained on iris samples, they better identify the difference between real iris micro-structures and the external texture created by the textured lens. The proposed approach outperforms several existing methods and offers substantially improved performance benchmarks for the problem. However, this method emphasizes merely the textured lens-based PAs, but other substances are also available to perform iris presentation attacks, such as printed iris, artificial eyeballs, synthetic iris, scanned copy of printed iris, etc. Therefore, the next chapter shall focus on a variety of such known and unknown presentation attacks and the PAD mechanism.

CHAPTER-4: Iris PAD using Best-k Feature Selection from YOLO based RoI[3]

4.1 Introduction

This chapter emphasizes developing a novel iris PAD method that includes a medley of known and unknown iris presentation attacks. Figure 4.1 depicts various types of iris PAs along with corresponding real/genuine iris images. The majority of existing methods analyze the entire eye image to classify real iris and an attack [3, 5]. However, many PAs don't alter the entire eye image; instead, merely the iris region is affected. It infers that the iris embodies the region of interest (RoI) for key feature analysis. The proposed iris PAD method locates RoI using the You Only Look Once (YOLO) approach.

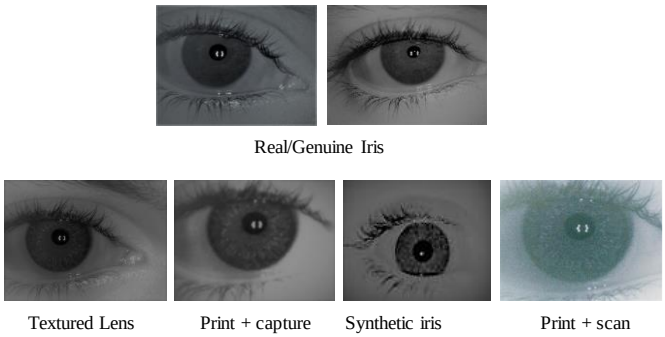


Fig. **4.1** Depiction of various iris presentation attack samples (bottom row) corresponding to live iris (top row).

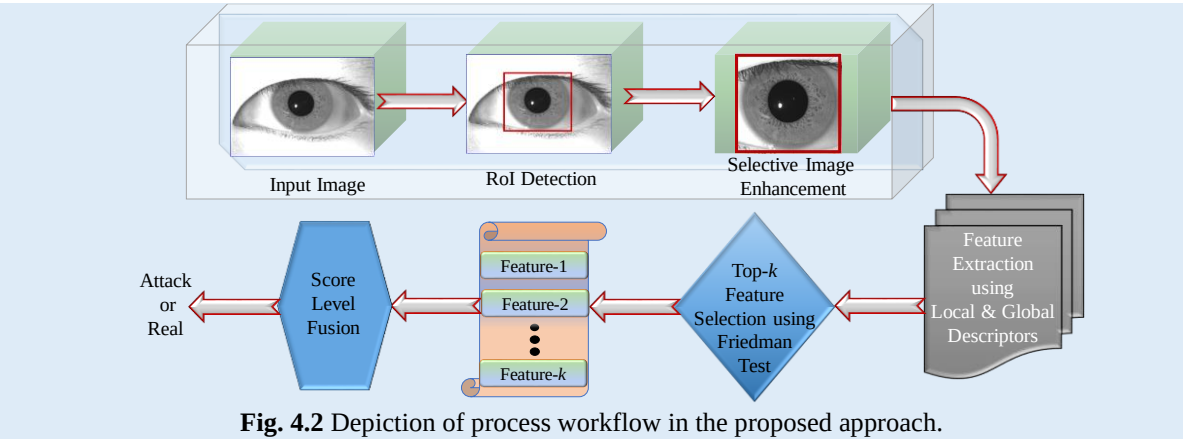


Fig. 4.2 Depiction of process workflow in the proposed approach.

4.2 Proposed Method: Best-k Feature Selection and Fusion from YOLO based RoI

Figure 4.2 illustrates the proposed iris PAD approach. Begin with Region of Interest (RoI) localization through DarkNet-19 model based on the YOLO approach [20]. It next performs selective image enhancement on the RoI through rescaling, sharpening, color, and contrast variation, etc. Further, seven distinct feature extractors were used to constitute features from enhanced RoI, and the Friedman test [21] was used to accomplish best-k feature selection from resultant features. Furthermore, the selected features are combined using score-level fusion to make a final attack prediction.

4.3 Experimental Setup and Results

[3] Choudhary, M., Tiwari, V. and Uduthalapally, V., 2020. Iris presentation attack detection based on best-k feature selection from YOLO inspired RoI. Neural Computing and Applications, pp.1-21.

4.3.1 Datasets

The proposed method is evaluated on six iris PAD datasets; IIITD Contact Lens Dataset (CLD) [14], IIITD Combined Spoofing Dataset (CSD) [7], ND-LivDet-2017 [15], ND Contact Lens 2013 [13], LivDet-Iris-2015 Clarkson [15], and LivDet-Iris-2017 Clarkson [15]. Further, Single-sensor and Cross-sensor validation protocols are also included for performance assessment. A cross-dataset validation is also included, where different datasets are considered as train-test pairs to validate the likelihood of transfer learning through these datasets.

4.3.2 Best-k Feature Selection through Friedman Test

The Friedman test [21] compares seven distinct algorithms; SIFT, LBP, MBSIF, CoA LBP, Haralick features, Zernike moments, and VGG-8 on 18 datasets using the Friedman test. Figure 4.3 illustrates the outcome of the post-hoc tests, where it is perceived that SIFT [4], VGG-8 [6], and MBSIF [19] features report best classifications. Thus, they are combined using score-level fusion [5] to obtain the final output.The single-sensor and cross-sensor assessment of the proposed method is illustrated in Table 4.1 and Table 4.2, respectively in terms of EER. The cross-dataset evaluation is given in Table 4.3

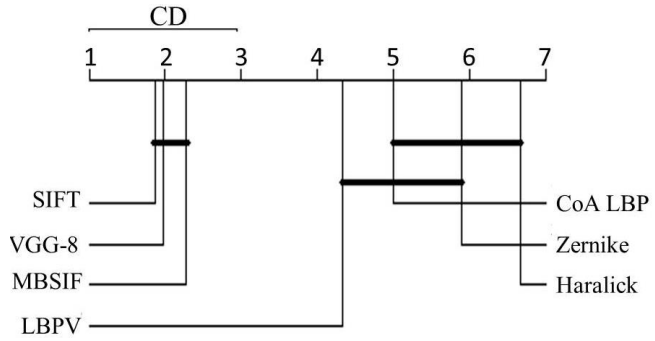


Fig. 4.3 Friedman test and Nemeny test Outcome.

Table 4.1. Error rates resulted by the proposed approach within single-sensor domain.

Datasets	EER (%)
IIITD CLD	1.07
ND CLD	2.02
ND LivDet	2.92
IIITD CSD	1.62
Clarkson 2015	3.85
Clarkson 2017	3.25

Table 4.2 Results for Cross-sensor Evaluation

Cross-sensor Pair	Accuracy	APCER	BPCER	ACER	EER
IIITD-Congent → IIITD-Vista	99.88	3.22	0.19	1.70	2.86
IIITD-Vista → IIITD-Congent	98.75	4.08	2.15	3.11	3.09
ND-I → ND-II	98.21	2.93	1.36	2.14	1.87
ND-II → ND-I	97.53	4.79	3.91	3.25	4.68
LG → Dalsa	86.31	7.89	4.25	6.07	5.93
Dalsa → LG	82.54	9.01	3.92	6.46	7.19

Table 4.3 Results for Cross-Dataset Evaluation

Cross-Dataset Pair	Accuracy	APCER	BPCER	ACER	EER
IIITD-CLD→ IIITD CSD	73.71	12.03	18.61	15.32	16.07
ND LivDet→ ND CLD	70.21	18.23	20.08	20.15	22.10
IIITD → ND	63.43	27.02	20.24	23.63	27.64
Clarkson→ *	Random prediction				

* represent any dataset

4.4 Summary

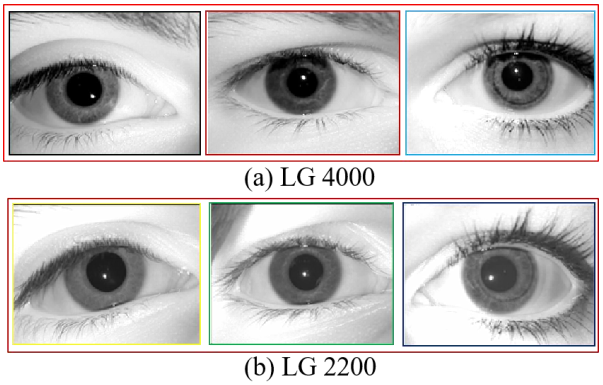
This chapter introduces an iris PAD method to discriminate real iris and medley of known and unknown iris PAs that can be launched at the sensor level. This work also suggests exploiting the Friedman test for feature selection. The experimental analysis reveals that our method works exceptionally well for intra-sensor validation. However, cross-domain iris PAD still needs improvement.

The aforementioned work focuses on iris PAD towards alleviating issues in iris-based human recognition. However, apart from presentation attacks, an iris recognition system also faces difficulties when heterogeneous sensors are used for iris acquisition in an unconstraint environment. This problem is explored in the next chapter along with the countermeasures.

CHAPTER-5: Enhancing Iris Recognition Performance in Unconstraint Environment[4]

5.1 Introduction

Unconstrained image acquisition through heterogeneous sensors has been a significant obstacle in the wide-scale deployment of IR systems [2]. The textural qualities of iris samples (images) captured through distinct sensors substantially differ due to the differences in illumination and the underlying hardware that yields intra-class variation within the iris dataset. Figure 5.1 depicts the iris images captured using two different sensors, i.e., LG4000 and LG2200. The variance in qualities of iris images eventually increases the false rejection rate (FRR) [8]. This chapter introduces a "Collaborative Convolutional Residual Network (CCRNet)" and ensembles it with two preeminent feature extraction methods, i.e., scale-invariant feature transform and binarized statistical information features using score-level fusion. The proposed approach is evaluated on two iris datasets; ND-CrossSensor-Iris-2013 and ND-iris-0405.



(a) LG 4000

(b) LG 2200

Fig. 5.1 Iris images from two heterogeneous sensors, (a) LG4000 and (b) LG2200.

5.2 Proposed Methodology: Collaborative Convolutional Residual Network (CCRNet)

The cross-sensor iris recognition aims to recognize individuals whose iris samples are captured using heterogeneous sensors. The proposed framework to enrich cross-sensor iris recognition is delineated in Fig. 5.2. It is designed with interleaved arrangements of convolutional and residual layers and thus named as "Collaborative Convolutional Residual Network (CCRNet)". Further, this model is combined with two additional handcrafted feature extractors, i.e., scale-invariant feature transform (SIFT) [4] and BSIF [17]. The respective outcomes are combined using score-level fusion [3] to get the final output.

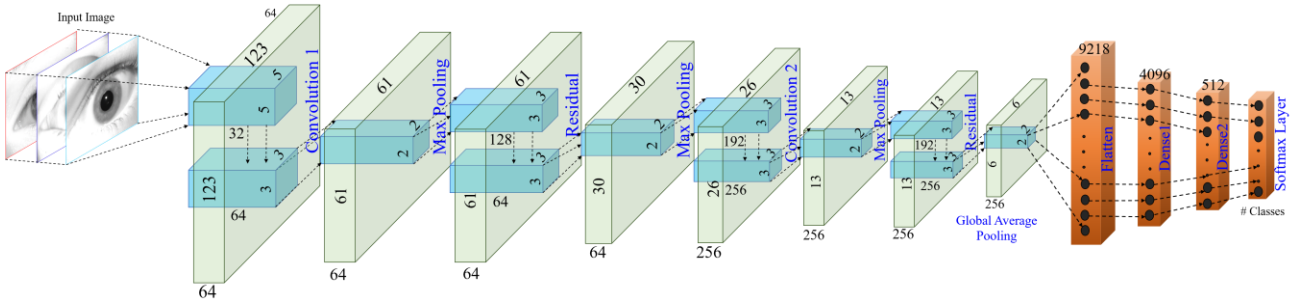


Fig. 5.2 The proposed CCRNet model's architecture.

[4] Choudhary, M., Tiwari, V. and Venkanna, U., 2020. CCRNet: a novel data-driven approach to improve cross-domain Iris recognition. Multimedia Tools and Applications, 79(43), pp.32807-32831.

5.3 Experimental Setup and Results

5.3.1 Datasets

- ND-Iris-0405-Dataset
- ND-CrossSensor-Iris-2013 Dataset

Table 5.1 describes the aforementioned databases in terms of the total number of samples (images) from various iris subjects.

Table 5.1 Summary of Iris Databases

Dataset	# classes	# images
ND-0405	712	64980
LG4000	1352	29986
LG2200	1352	116564

Table 5.2 Databases splitting in blocks

	Split of ND-0405		Split of LG4000		Split of LG2200	
	# classes	# images	# classes	# images	# classes	# images
Group-1	174	26586	626	14106	196	26586
Group-2	280	28753	445	9920	572	30879
Group-3	190	7786	281	5960	269	9576

5.3.2 Dataset Splitting

Each dataset is split into three groups based on iris subjects with a decreasing number of images. In specific, group-1 encompasses iris subjects with the maximum number of images, while, group-3 contains subjects with minimum iris images. Similarly, group-2 includes the subjects with an average number of iris samples. Such partitioning at the sensor level is aimed to balance the image distribution among iris subjects in each group. Accordingly, the image distribution into groups for ND-0405, LG2200, and LG4000 sensor datasets is demonstrated in Table 5.2.

Single-sensor Dataset Creation: In Single sensor validation, training and testing are carried out on samples from the same sensor. Table 5.3 summarizes five distinct experiments where training, validation, and testing sets are prepared from the same sensor.

Cross-sensor Dataset Creation: In this experimental setup, training and probe sets are generated from a distinct couple of groups, as listed in Table 5.4. Here, five experiments are designed to assess the proposed method for cross-sensor iris recognition.

Table 5.3 Single-sensor dataset setup

Exp.	Training and Validation				Testing		
	Dataset	#subjects	Train-set	Validation-set	Dataset	Probe-set	# subjects
1	ND-0405	174	19142	2126	ND-0405	5318	110
2	LG-2200	572	27791	3088	LG-2200	6176	145
3	LG-4000	281	5364	596	LG-4000	1192	55
4	ND-0405	174	23927	2659	LG-2200	5318	92
5	LG-2200	269	8619	957	ND-0405	1914	60

Table 5.4 Cross-sensor dataset setup

Exp.	Training and Validation				Testing		
	Dataset	Iris subjects	Training set	Validation	Dataset	Probe set	Iris subjects
1	LG-2200	196	23927	2659	LG-4000	1457	47
2	ND-0405	280	25878	2875	LG-4000	2106	78
3	LG-4000	281	5364	596	LG-2200	1275	75
4	ND-0405+ LG-4000	280+281	25878+5364	2875+596	LG-2200	9688	173
5	LG-2200+ LG-4000	196+281	23927+5364	2659+596	ND-0405	5655	145

Table 5.5 CCRNet performance on Experiments for Iris Recognition in Single-sensor

Experiments	EER%
Exp1	2.19%
Exp2	4.13%
Exp3	3.40%
Exp4	1.14%
Exp5	3.80%

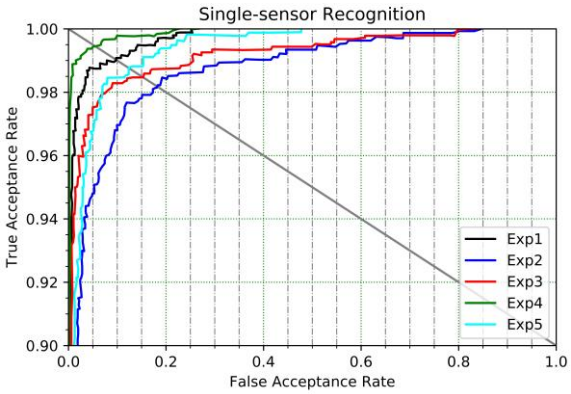


Fig. 5.3 ROC curves depicting CCRNet performance for various experiments of single-sensor iris recognition.

Table 5.6 Proposed model's performance for Iris Recognition in Cross-sensor

Experiments	EER%
Exp1	1.21
Exp2	1.06
Exp3	2.80

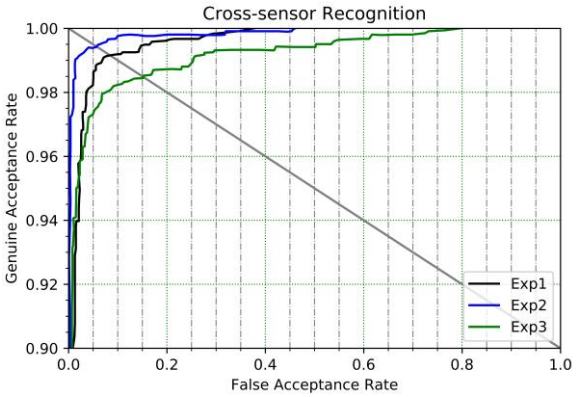


Fig. 5.4 ROC curves depicting *CCRNet* performance on various experiments for iris recognition in Cross-sensor.

5.3.3 Experimental Outcomes

Single-sensor Recognition: The assessment of the proposed CCRNet model begins with single-sensor iris recognition, where it is used to simulate the experimental setup given in Table 5.5. Fig. 5.3 demonstrates the outcomes reported by CCRNet for each experiment in terms of EER and ROC curves.

Cross-sensor Recognition: The CCRNet model is further assessed for cross-sensor recognition by simulating the experiments delineated in Table 5.4. Table 5.6 and Fig. 5.4 show the results for the first three experiments: Exp1, Exp2, and Exp3. Whereas, for Exp4 and Exp5, results are described in the next subsection.

5.4 Summary

This chapter attempts to enrich heterogeneous-sensor iris recognition using an ensemble model containing CCRNet with two handcrafted methods. Further, the CCRNet is configured to exploit pre-activation that substantially aids in improving the CCRNet's performance. Experimental results depict that it exhibits favorable cross-sensor recognition performance by significantly dropping the error rate and outperforms the state of the arts. In future work, the cross-dataset setup can be explored to enhance the scalability of iris recognition further.

This chapter has restricted the cross-sensor iris recognition, where iris acquisition is carried out in the NIR spectrum. However, a more challenging task is to enrich visible iris recognition, where iris images are captured using visible wavelength. Since the iris texture is not identifiable in such images, it's quite difficult to achieve a high true recognition rate. This problem is comprehensively explored in the next chapter.

CHAPTER-6: Visible Spectrum Iris Verification in Smartphones using Sandwiched Siamese Framework

6.1 Introduction

The advent of smartphone devices and mobile internet has made smartphone-based iris recognition a prominent user authentication mechanism. However, visible light based iris acquisition results in iris images with unidentifiable iris texture that diminishes the iris recognition performance [9, 11]. This chapter introduces a new iris verification scheme based on a sandwiched Siamese architecture, which examines normalized iris pairs and learns a similarity score based on their relational features. Besides, the proposed framework handles the challenges caused by visible light, partial occlusions, and illumination changes through a normalized correlation layer.

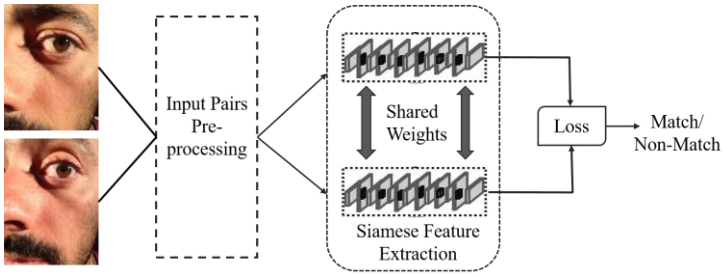


Fig. 6.1 Illustration of Proposed Scheme**.**

6.2 Proposed Approach: Sandwiched Siamese Model for Iris Similarity Learning

In general, iris verification is also termed iris matching, where the similarity between two iris images is measured through several means [3]. Since this work includes some noisy iris samples, an extensive preprocessing phase is followed to remove noise and make iris samples suitable for feature extraction. Afterward, normalized iris image pairs are input to a sandwiched Siamese model for feature extraction and similarity function approximation. The model is trained on both positive (same irises) and negative (distinct irises) image pairs and returns a likelihood of their belonging to the same person. Figure 6.1 outlines the abstract view of the proposed scheme for better understanding.

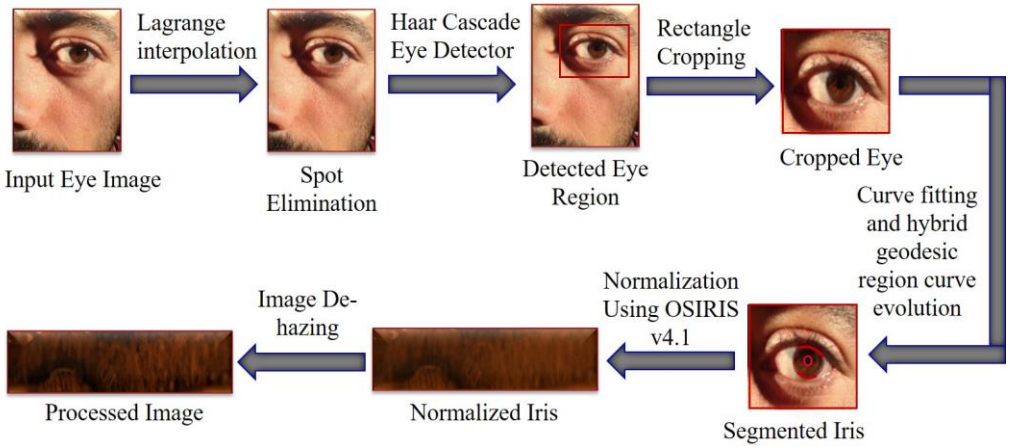


Fig. 6.2 Illustration of various Input Preprocessing steps.

6.2.1 Input Pre-processing

The unconstrained iris acquisition through the smartphone camera captures the entire periocular image, thus, we need to detect the region of interest [10]. Besides, the outdoor acquisition results in occlusion and reflection on the iris region and yields important feature loss. Therefore, we remove the light spot from the iris region by using the Lagrange interpolation method, then the iris region is segmented using fitting circle method based on the gray gradient information. Finally, the segmented region is normalized using OSIRIS v4.1. Besides, an image dehazing is applied to make the iris texture clear. Figure 6.2 represents the sequence of pre-processing steps included in the proposed scheme.

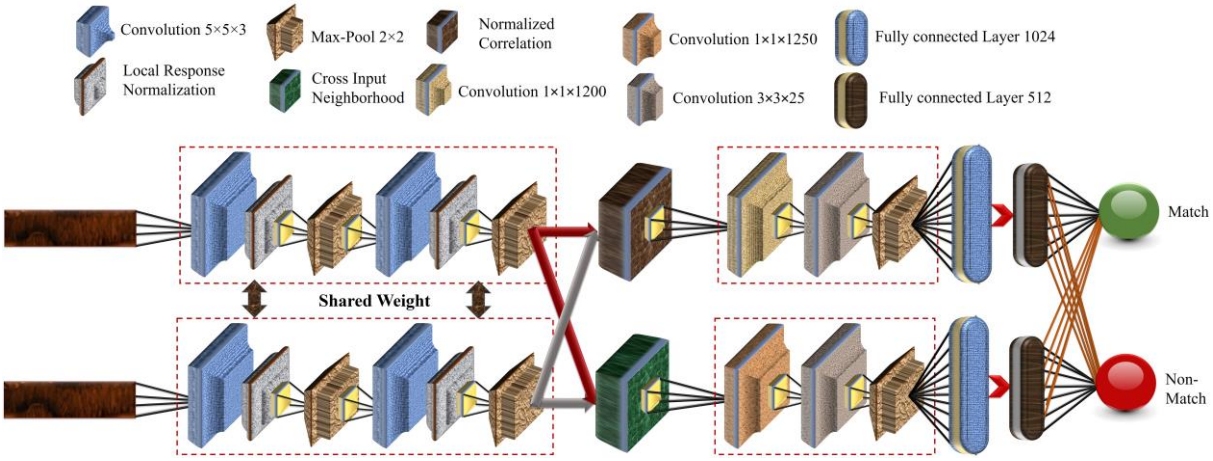


Fig. 6.3 Proposed Sandwiched Siamese Model

6.2.2 Sandwiched Siamese model Architecture

The feature extraction module is inspired by the Siamese architecture, where two identical CNN models work in parallel such that the weight update is mirrored across both models as depicted in Fig. 6.3. Since the iris contains micro-features harder to represent and distinguish, we developed a sandwiched Siamese architecture using a variety of layers with diverse functioning to extract important textural details from the image pairs and to learn the similarity function.

6.3 Experimental Setup and Results

6.3.1 Datasets

- MICHE-I Dataset [22]
- MICHE-II Dataset [23]

6.3.2 Experiments on MICHE-I Dataset

The experimental outcomes on the images acquired through iPhone 5 and Samsung Galaxy S4 cameras in the MICHE-I dataset are demonstrated in Table 6.1 and Table 6.2, respectively. The experiments follow the same validation protocols and the performance metrics utilized in the reference papers of the existing methods.

Table 6.1 Performance comparison for iPhone 5 (MICHE-I). Here, GMR is calculated at fixed FMR=0.1%.

Technique	Indoor_Front		Indoor_Rear		Outdoor_Front		Outdoor_Rear	
	EER%	*GMR*	*EER%*	*GMR*	*EER%*	*GMR*	*EER%*	*GMR*
Deep Sparse Features [9]	2.08	77.08	6.25	64.58	4.19	79.17	25.29	56.25
MDSH + Cosine [10]	5.77	77.43	10.16	75.69	4.12	88.54	7.37	77.43
MDSH + Chi-sqr [10]	5.23	86.11	8.06	84.38	1.81	94.44	7.15	75.35
MDSH + collaborative [10]	2.09	95.49	1.73	95.49	0.37	98.61	1.17	95.49
MAC + CRC [11]	0.21	98.81	4.39	89.13	3.18	91.45	4.77	89.11
Proposed	**0.83**	**97.12**	**1.60**	**94.37**	**0.17**	**99.33**	**0.97**	**97.15**

Table 6.2 Performance comparison for Samsung Galaxy S4 (MICHE-I). GMR is computed at fixed FMR=0.1%

Technique	Indoor_Front		Indoor_Rear		Outdoor_Front		Outdoor_Rear	
	EER%	*GMR*	*EER%*	*GMR*	*EER%*	*GMR*	*EER%*	*GMR*
Deep Sparse Features [9]	2.50	81.25	3.97	87.50	6.27	72.92	2.06	85.42
MDSH + Cosine [10]	2.91	91.32	8.43	82.64	3.48	91.32	6.97	81.60
MDSH + Chi-sqr [10]	4.70	89.93	8.65	85.07	1.84	95.14	7.34	76.39
MDSH + collaborative [10]	1.41	96.18	2.46	92.71	0.66	97.92	1.17	95.14
MAC + CRC [11]	2.25	94.79	2.90	94.66	4.04	88.99	2.50	93.76

Table 6.3 Proposed model's performance on MICHE-II dataset in terms of Recognition Rate (%).

Algorithm	All vs All	Known vs Known	Unknown vs Unknown	Unknown vs All + All vs Unknown
MDSH + Cosine [10]	92.07	94.93	82.50	85.77
MDSH + Chi-sqr [10]	90.13	92.17	84.12	87.33
MDSH + collaborative [10]	98.43	99.23	96.32	98.62
MAC + CRC [11]	87.88	92.41	86.69	88.02
IB1 [24]	98.14	99.93	90.08	96.69
Proposed	**99.11**	**100**	**97.93**	**99.19**

6.3.3 Experiments on MICHE-II Dataset

The outcomes of comparative analysis on the MICHE-II dataset are mentioned in Table 6.3 in terms of genuine match rate (GMR %) at 0.1% FMR.

6.4 Summary

In this chapter, a sandwiched Siamese model is introduced to compute the similarity between pairs of normalized iris images. The design of the sandwiched Siamese model also emphasizes handling illumination changes and thus incorporates a normalized correlation layer to preserve the correlation information in the search space of tiny image patches and constitute features from the local neighborhood of the pixels. The spatial correlation across neighborhood differences is obtained through cross-patch feature representation by a sequence of convolutional and pooling layers.

The proposed scheme is evaluated on MICHE-I and MICHE-II Datasets and compared with the state-of-the-art iris recognition methods as well. The experimental outcomes reveal that the proposed method is robust against the variation in the illumination conditions and the type of camera/sensor. Further, it adopts the unconstraint iris acquisition without compromising the verification accuracy. The comparative analysis validates the dominance of the proposed method over existing performance benchmarks.

CHAPTER-7: Conclusion and Future Scope

This study explores iris biometrics and attempts to overcome the underlying challenges preventing worldwide adoption of iris recognition technology. A comprehensive literature analysis unveils some critical issues that encounter either when iris recognition systems are in processing, or in cases where such systems need to be deployed under limited supervision and/or an unconstrained environment. Iris based person recognition has been incorporated in large-scale systems such as India's Adhaar program, Amsterdam's airport, and US/Canadian border, forensic labs, etc., due to its inimitable features such as iris microstructures possess uniqueness over immense population (even twins), stability over time, improbable to be damaged by surrounding factors. Moreover, it is nearly impossible to generate iris features of an individual through artificial means, even unlike fingerprints, iris features cannot be copied through any physical substances. However, iris recognition is critically influenced by several important factors that need more exploration from researchers. In this study, we have focused on four distinct problems related to iris recognition, i.e. iris contact lens discrimination, iris presentation attack detection, cross-domain iris recognition, and iris recognition with visible spectrum-based iris imaging. Consequently, the conceptual and experimental study yielded some important observations, which are described in this chapter.

Iris recognition technology still embraces various loopholes to compromise the recognition performance. This study has focused on four distinct problems to either remove or reduce their impact on the working of iris recognition systems. Although the proposed work has succeeded to mitigate the existing issues, there is still scope for improvement in each phase. For instance, cosmetic contact lens detection has been successfully performed through some existing methods even in cases where distinct sensors are used for iris imaging. However, cross-dataset evaluation still needs improvement. Besides, soft lens detection with single and cross-sensor is failed to achieve accurate results. Therefore, attaining flawless iris contact lens detection with the cross-sensor environment is an open topic of research.

In this entire study, we have explored four distinct problems related to iris recognition and developed a dedicated methodology to mitigate an individual problem. However, an iris recognition system may require an all-in-one solution capable to handle each of them. Therefore, in future work, we shall attempt to build a composite framework with the proposed methodologies to deploy it as a robust iris recognition system in real-world applications.

Organization of Thesis

A detailed description of each chapter is given below:

Chapter-1

This chapter discusses the background of iris biometrics and describes various underlying challenges including unconstrained iris acquisition through heterogeneous sensors, the iris presentation attacks, and invisibility of iris features in the visible spectrum.

Chapter-2

This chapter emphasizes textured lens based presentation attack detection and iris contact lens discrimination. It introduces a Densely-connected Contact-lens Classification Network (DCCNet), and its fusion with two handcrafted methods; SID and DAISY using score-level fusion. The fused model is evaluated on public iris datasets using three validation protocols.

Chapter-3

This chapter explores iris presentation attack detection (PAD) and contact lens classification and proposes the score-level fusion of two domain-specific feature extraction methods. In specific, the deep-learning model and multi-scale BSIF filters both explicitly trained on iris images. The method is compared with SoTA handcrafted and deep-learning based methods based on public iris datasets.

Chapter-4

This chapter focuses to improve the iris recognition system's performance in an unconstrained environment, where heterogeneous sensors are used for iris acquisition. Moreover, a Collaborative Convolutional Residual Network (CCRNet) is developed and ensemble with SIFT and BSIF methods. The model is evaluated on cross-sensor iris datasets, which surpasses the existing benchmarks.

Chapter-5

This chapter emphasizes iris presentation attack detection (PAD), which includes a medley of known and unknown attacks. It demonstrates an iris PAD mechanism, where the DarkNet-19 model is used to detect the Region of Interest (RoI). Afterward, three feature extraction methods are employed to extract important features from the RoI. The method is compared with SoTA methods on public iris datasets.

Chapter-6

This chapter introduces a new iris verification scheme for user authentication in smartphones, where iris acquisition is carried out using smartphone cameras with visible wavelength. It introduces a sandwiched Siamese model, which examines normalized iris pairs and learns a similarity score based on their relational features. The proposed approach is evaluated on two public iris datasets and compared with three SoTA methods.

Chapter-7

This chapter describes the conclusion drawn from the entire work and also mentions the advantages and shortcomings of each proposed method. It also discusses the future scope within the iris recognition research domain.

List of Publications

Published Articles

1. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Iris Liveness Detection using Fusion of Domain-specific Multiple BSIF and DenseNet Features", IEEE Transactions on Cybernetics, pp. 1-12, 2020, (SCI, Impact Factor: 11.079).
2. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Iris anti-spoofing through score-level fusion of handcrafted and data-driven features. Applied Soft Computing, Vol. 91, pp.106-206, 2020, (SCI-E, Impact Factor: 5.472).
3. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Iris presentation attack detection based on best-k feature selection from YOLO inspired RoI", Neural Computing and Applications, Springer, pp.1-21, 2020, (SCI, Impact Factor: 4.774).
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6. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "An Approach for Iris Contact Lens Detection and Classification Using Ensemble of Customized DenseNet and SVM", Future Generation Computer Systems (FGCS), Elsevier, Vol. 101, pp. 1259-1270, 2019, (SCI-E, Impact Factor: 6.125).

Communicated Articles

1. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Sandwiched Siamese Model based Visible Light Iris Verification for Low-Powered Devices", Pattern Recognition, Elsevier, Feb 2021.
2. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Identifying Discriminatory Feature-vectors for Fusion-based Iris Liveness Detection", Journal of Ambient Intelligence & Humanized Computing, Springer, Jan 2021.
3. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Person Re-identification using Deep Siamese Network with Multi-layer Similarity Constraints", Multimedia Tools and applications, Springer, April 2021.

Published Conferences

1. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Unraveling Deep Learning Performance in Cross-Sensor Iris Recognition", 2nd International Conference on Data Science, Machine Learning and Applications, ICDSMLA 2020, Pune, Maharashtra, India, Springer, 21-22 Nov 2020.
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4. Meenakshi Choudhary, Vivek Tiwari, Venkanna U., "Ensuring Secured Iris Authentication for Mobile Devices", 39th International Conference on Consumer Elecronics, ICCE 2021, USA, IEEE 11-12 Jan, 2021.

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